International Journal of Academic Multidisciplinary Research (IJAMR)
ISSN: 2643-9670
Vol. 10 Issue 7 July - 2026, Pages: 659-662

Artificial Intelligence and Computer Vision Approaches for Automated Waste Classification: A Systematic Review

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Abstract: *Rapid urbanization and rising municipal solid waste generation have made source segregation a central challenge for cities in developing regions, where mixed-waste disposal undermines recycling, causes economic loss, and creates environmental and public-health hazards. Artificial Intelligence (AI) and Computer Vision, particularly Convolutional Neural Networks (CNNs) and transfer learning, have emerged as promising tools for automating waste identification from digital images. This paper presents a systematic review of empirical research on AI-based waste classification, tracing its evolution from early sensor- and feature-based machine learning methods, through the deep learning and transfer learning era, to recent hybrid, ensemble, and multi-modal approaches. The review synthesizes the data-related, model-related, and deployment-related challenges reported across studies, together with the augmentation, transfer learning, ensemble, compression, and domain-adaptation strategies proposed to address them. Five research gaps are identified: limited research in East African contexts, weak integration between model development and end-user applications, the absence of standardized real-world benchmarks, insufficient study of user trust, and a shortage of models optimized for low-resource hardware. The review concludes by outlining a design-science research direction, illustrated through an ongoing project in Iringa, Tanzania, that responds directly to these gaps.*

Keywords—component; *waste classification, artificial intelligence, computer vision, convolutional neural networks, transfer learning, recycling, sustainable waste management.*

1.0 INTRODUCTION

Effective waste management is one of the most pressing environmental challenges confronting urban centers worldwide, with the burden falling disproportionately on developing nations. Rapid urbanization and population growth in cities such as Iringa, Tanzania, have driven a proportional rise in daily solid-waste generation, while the pervasive practice of commingling diverse waste types at the point of disposal continues to complicate recycling, raise processing costs, accelerate landfill depletion, and worsen environmental degradation.

The absence of source segregation carries multifaceted consequences: contamination of water sources through leachate percolation, air pollution from the incineration of mixed waste, progressive soil degradation, and elevated public-health risk for waste handlers and nearby communities. A foundational step toward mitigating these interlinked problems is the accurate identification and separation of waste into core categories such as plastic, paper, metal, glass, and organic matter.

Recent advances in Artificial Intelligence and Computer Vision offer a transformative route to this problem by enabling systems that automatically recognize and classify objects from digital images. This review examines the empirical literature on AI-driven waste classification to establish what has been achieved, what challenges persist, and where genuine research gaps remain, providing the evidentiary foundation for the development of an Intelligent Waste Classification System targeted at the East African context.

2.0 REVIEW METHODOLOGY

This review synthesizes empirical studies on AI- and computer-vision-based waste classification published between 2012 and 2025, drawn from peer-reviewed journals, conference proceedings, and benchmark dataset papers. Studies were selected for their methodological contribution (novel architectures, datasets, or deployment strategies) and empirical rigor (reported accuracy, precision, recall, or equivalent metrics on a defined test set). The literature is organized chronologically to trace the progression from traditional machine learning to deep learning, transfer learning, and ensemble or multi-modal methods, and is then synthesized thematically around the challenges and solutions reported across studies.

3.0 EVOLUTION OF AI-BASED WASTE CLASSIFICATION

3.1 Early Foundational Studies (2012–2015)

The earliest applications of machine learning to waste classification relied on traditional algorithms and handcrafted features. Arebey et al. [11] combined color and ultrasonic sensors with a Support Vector Machine classifier for automated solid-waste sorting, achieving acceptable accuracy for basic separation but limited scalability due to its dependence on physical sensors rather than visual data. A related study employed a K-Nearest Neighbors algorithm with texture and color features, reporting approximately 78% accuracy that degraded substantially under varying lighting conditions. These studies established the technical feasibility of automated classification while exposing the sensitivity of traditional approaches to environmental variability and their reliance on labor-intensive feature engineering.

3.2 The Deep Learning Revolution (2016–2019)

The availability of large annotated datasets, advances in GPU computing, and the maturation of CNN architectures drove a paradigm shift from 2016 onward. A landmark study applied a custom CNN to the TrashNet dataset (approximately 2,500 images across six categories), achieving 87.5% accuracy and demonstrating that CNNs could learn discriminative features automatically. Thung and Yang [7] subsequently compared AlexNet, VGG16, and ResNet50 on the same dataset, finding that deeper architectures consistently outperformed shallower ones, with ResNet50 reaching 88.5% accuracy; their error analysis revealed persistent confusion between visually similar categories such as clear plastic and glass, or brown paper and cardboard. Another study extended this line of work to real-time industrial sorting using a modified YOLOv3 detector, achieving 45 frames per second at 82.3% mean Average Precision, demonstrating the feasibility of AI-based classification under conveyor-belt conditions.

3.3 Transfer Learning and Lightweight Models (2020–2022)

As the field matured, two practical constraints, the scarcity of large labeled waste datasets and the need for models deployable on mobile or embedded devices, drove the adoption of transfer learning and efficient architectures. Aral et al. [10] fine-tuned VGG16, VGG19, ResNet50, InceptionV3, and MobileNet (pre-trained on ImageNet) on TrashNet, finding that MobileNet achieved 92.3% accuracy despite far fewer parameters than the larger models, establishing it as a strong candidate for mobile deployment. Bobulski and Kubanek [12] focused specifically on smartphone-based classification, collecting a custom dataset of 10,000 images under realistic conditions and achieving 89.7% accuracy with a modified MobileNetV2, underscoring the gap between controlled laboratory datasets and real-world deployment conditions.

3.4 Hybrid, Ensemble, and Multi-Sensor Approaches (2023–Present)

Most recently, researchers have combined multiple AI techniques or fused vision with other sensor modalities to improve robustness. Majchrowska et al. [4] introduced the TACO dataset, over 6,000 images of litter in complex outdoor environments, and benchmarked Faster R-CNN, YOLOv5, and DETR on it; the best model, YOLOv5x, reached only 65.4% mean Average Precision, substantially below TrashNet-based results, revealing a considerable gap between laboratory and real-world performance. A subsequent study addressed this gap with an ensemble of three parallel CNNs trained across TrashNet, TACO, and a custom dataset, achieving 94.2% accuracy and maintaining above 80% accuracy under cross-dataset validation. A more recent study combined visual data with near-infrared spectroscopy to resolve persistent ambiguities between clear plastic and glass, reaching 97.1% accuracy on a deliberately challenging test set, though at the cost of additional sensor hardware.

Table 1 summarizes representative accuracy benchmarks reported across this progression.

Study / Period	Method	Dataset
KNN with texture/color features (2012–2015)	K-Nearest Neighbors	Custom based)
Custom CNN on TrashNet (2016–2019)	Convolutional Neural Network	TrashNe
Thung & Yang [7]	AlexNet / VGG16 / ResNet50	TrashNe
Modified YOLOv3	Real-time object detection	Industria
Aral et al. [10] (2020–2022)	VGG16/19, ResNet50, InceptionV3, MobileNet (transfer learning)	TrashNe
Bobulski & Kubanek [12]	Modified MobileNetV2	Custom (10,000
Majchrowska et al. [4] (2023–present)	Faster R-CNN / YOLOv5 / DETR	TACO (outdoor
Ensemble of three CNNs	Ensemble learning	TrashNe dataset
Multi-modal vision + NIR	CNN + near-infrared spectroscopy fusion	Challeng vs. glass

4.0 CHALLENGES IN AI-BASED WASTE CLASSIFICATION

4.1 Data-Related Challenges

Many studies, particularly early ones, relied on small datasets, TrashNet contains only about 2,500 images, which increases the risk of overfitting and limits generalization to new lighting, background, and item conditions. Waste datasets also frequently exhibit class imbalance, biasing models toward overrepresented categories such as plastic bottles, and manual annotation of ambiguous items introduces label noise that is rarely quantified through inter-annotator agreement metrics.

4.2 Model-Related Challenges

The TACO benchmark starkly illustrates a generalization gap: models exceeding 90% accuracy on controlled datasets can drop to 65–70% on real-world images. Certain category pairs, clear plastic versus glass, brown paper versus cardboard, aluminum versus steel, consistently produce high error rates because they share visual features such as color, texture, and reflectivity. High-accuracy architectures such as ResNet152 or ensembles further impose computational costs that conflict with real-time, resource-constrained deployment.

4.3 Deployment and Operational Challenges

Real-world deployment introduces variability, changing lighting, partial occlusion, variable camera angle, and wet or

International Journal of Academic Engineering Research (IJAER)
ISSN: 2643-9085
Vol. 2026, Pages: 1-4
www.ijeais.org/ijaer

degraded items, that is difficult to anticipate during model development. Integrating a well-performing model into existing waste-management workflows raises further practical issues of hardware compatibility, bandwidth, and latency, while public-facing applications additionally depend on sustained user trust, which erodes quickly if the system makes frequent visible errors.

5.0 SOLUTIONS PROPOSED IN THE LITERATURE

5.1 Addressing Data Limitations

Data augmentation, random rotation, flipping, scaling, and brightness or contrast adjustment, has been shown to expand effective training-set size and typically improves test accuracy by 3–5%. Transfer learning reduces the labeled-data requirement by reusing general visual features learned on large datasets such as ImageNet. More recent work has explored active and semi-supervised learning to reduce annotation burden while preserving performance.

5.2 Addressing Model Limitations

Ensemble methods combining several diverse models typically yield 2–4% higher accuracy than any single constituent model. Attention mechanisms allow models to focus on informative image regions despite clutter or occlusion, while neural architecture search has been used to automatically discover architectures with favorable accuracy-efficiency trade-offs.

5.3 Addressing Deployment Constraints

Model compression techniques, pruning, quantization, and knowledge distillation, can reduce model size five- to ten-fold with minimal accuracy loss, enabling mobile deployment. Domain-adaptation and adversarial training approaches aim to close the generalization gap between laboratory and field conditions, while multi-modal fusion (vision combined with near-infrared or thermal sensing) offers a path to near-perfect classification for visually ambiguous categories, at the cost of additional hardware.

6.0 RESEARCH GAPS

Synthesizing across the reviewed literature, five persistent gaps emerge.

6.1 Limited Research in East African Contexts

The great majority of empirical studies originate from high-income countries or South and Southeast Asia; East African contexts, including Tanzania, remain largely unstudied, despite substantial regional differences in waste composition, handling practices, and infrastructure.

6.2 Limited Integration of End-User Applications

Most studies report model performance metrics without implementing or evaluating a complete, user-facing system, leaving a gap between promising research findings and tools that communities can actually use.

6.3 Lack of a Standardized Real-World Benchmark

Most reported performance is measured on controlled datasets such as TrashNet; the TACO benchmark demonstrates that this does not predict real-world performance, yet no standardized real-world evaluation protocol has emerged.

6.4 Limited Study of User Trust and Acceptance

Few studies empirically investigate the factors, confidence scores, explanations, feedback mechanisms, that influence sustained user trust and adoption of public-facing classification tools.

6.5 Need for Models Optimized for Low-Resource Hardware

Existing lightweight-model research largely assumes access to modern smartphones or cloud infrastructure, leaving a gap in models explicitly optimized for the older, lower-specification devices common in developing-country contexts.

7.0 PROPOSED RESEARCH DIRECTION

These gaps motivate an ongoing design-science research project, the Intelligent Waste Classification System, being developed in Iringa, Tanzania. The project combines public datasets (TrashNet, TACO, and the Kaggle Waste Classification Data V2) with a custom local dataset of approximately 3,000 images to capture region-specific packaging, degradation patterns, and lighting conditions. Three transfer-learning architectures (MobileNetV2, ResNet50, VGG16) will be trained and compared using accuracy, precision, recall, F1-score, inference time, and model size, with the best-performing model deployed behind a lightweight web application for real-time classification. This work directly targets Gaps 1, 2, and 5 identified above, while its evaluation protocol, including a locally collected real-world test set and preliminary user-acceptance testing, contributes toward Gaps 3 and 4.

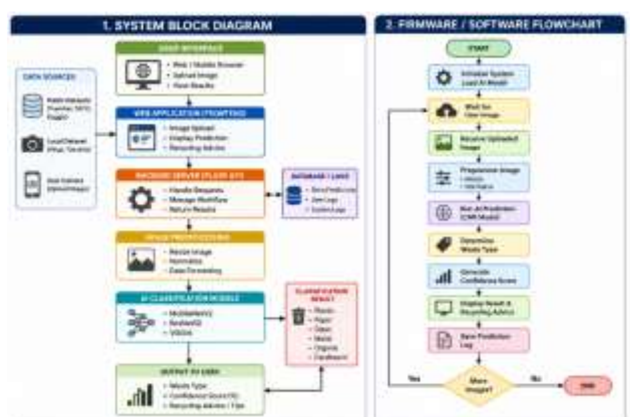

Figure 1:Block diagram and firmware flowchart of intelligent waste classification system

8.0 CONCLUSION

The empirical literature on AI-based waste classification demonstrates clear technical progress, from early sensor- and feature-based classifiers to deep transfer-learning and ensemble methods capable of exceeding 90% accuracy under controlled conditions. However, a persistent generalization gap between laboratory and real-world performance, together with limited geographic diversity, weak integration of end-to-end applications, and insufficient attention to user trust and low-resource deployment, constrain the field's practical impact. Addressing these gaps, particularly through regionally grounded datasets and complete, evaluated end-user systems, represents the most promising direction for advancing AI-based waste classification toward genuine adoption in developing-country contexts such as Tanzania.

9.0 ACKNOWLEDGEMENT

We would like to express our sincere gratitude to our project supervisor for guidance and support throughout the preparation of this review. We also thank our colleagues in the Department of Computer Science, Ruaha Catholic University, for their valuable suggestions and encouragement.

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